Chinese Character Recognition by Tchebichef Moment Features

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Abstract—Moment descriptors have long been applied in object recognition since the early years of the development of the moment theories. Nowadays, discrete orthogonal moments have been studied and proposed for they are superior to traditional continuous ones. In this paper, a set of moment features extracted from the discrete Tchebichef moments for Chinese character recognition is presented. A new method of evaluating the variance values of each moment feature is applied in this research. Tested on a set of 6,763 Chinese characters, our newly proposed Tchebichef moment features perform very well in distinguishing all Chinese character pairs that have similar structures.

Index Terms—Discrete orthogonal moments, tchebichef moments, Chinese character recognition.

I. INTRODUCTION

Since Hu [1] introduced the moment methods in 1961, moment descriptors have been widely used in image representation, pattern recognition, and object classification. One of the applications using moment features is the Chinese character recognition. Chinese characters are very different from many other languages in conveying information, while the structure of a character is a key to its meaning and pronunciation. Many feature extraction methods applied in the Chinese character recognition systems are based on the local features, such as strokes and feature points [2]–[5]. While the existing methods are quite efficient in general, there are some difficulties to distinguish two characters when they have very close structures. On the other hand, the moment method has the advantage of utilizing the global features of the Chinese characters, therefore, it can be used as a complementary scheme to overcome the obstacles confronted by other systems. Some Chinese character recognition systems based on the orthogonal moment descriptors have been reported [6]–[8]. Recently, the emergence of discrete orthogonal moments has substantially enriched the moment methods. Moments based on Tchebichef and Krawtchouk polynomials were introduced by Mukundan *et al.* [9] and Yap *et al.* [10] in 2001 and 2003, respectively. Since the computation of discrete orthogonal moments is not involved with numerical approximation of the weight function, while maintaining the property of orthogonal, the discrete moments are superior to traditional

continuous orthogonal moments in terms of calculation accuracy and speed. Since they were introduced, the discrete orthogonal moments have been productively utilized in image processing [11]–[13], pattern recognition [14], [15], and many other scientific field [16]. In this research, we have utilized the Tchebichef moments in the aspect of Chinese character recognition. Four lower orders Tchebichef moments with the highest variance values are selected as features in the four dimensional Tchebichef moment space. A set of 6,763 Chinese characters, which are defined in the Chinese standard GB2312, is used as the testing characters. Our results show that the recognition ability of the four features based on the Tchebichef moments overwhelms the ones utilizing continuous orthogonal moments.

II. TCHEBICHEF MOMENTS

The definition of the n -th order classical Tchebichef Polynomial is defined as

$$t_n(x) = (1-N) {}_3F_2(-n, -x, 1+n; 1, 1-N; 1) \quad (1)$$

where $x, n = 0, 1, 2, \dots, N, N > 0, p \in (0, 1)$. ${}_2F_1$ is the hypergeometric function. a_k is the Pochhammer symbol given by

$$(a)_k = a(a+1)\dots(a+k-1) = \frac{\Gamma(a+k)}{\Gamma(a)} \quad (2)$$

$${}_2F_1(a, b; c; z) = \sum_{k=0}^{\infty} \frac{(a)_k (b)_k}{(c)_k} \frac{z^k}{k!} \quad (3)$$

With the definitions above, (1) can also be written as

$$t_n(x) = n! \sum_{k=0}^n (-1)^{n-k} \binom{N-1-k}{n-k} \binom{n+k}{n} \binom{x}{k} \quad (4)$$

The scaled Tchebichef polynomials are defined as

$$t_n(x) = \frac{t_n(x)}{\beta(n, N)} \quad (5)$$

where $t_n(x)$ is the discrete Tchebichef polynomial given by (1), and $\beta(n, N)$ is a constant which is independent of x . Under the discussion above, the squared norm of the scaled polynomial is given by

$$p(n, N) = \frac{\rho(n, N)}{\beta(n, N)^2} \quad (6)$$

where $\rho(n, N)$ is

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$$\rho(n, N) = \frac{N(N^2 - 1)(N^2 - 2^2) \dots (N^2 - n^2)}{2n + 1} \quad (7)$$

$$= (2n)! \binom{N+n}{2n+1}, n = 0, 1, \dots, N-1$$

Which satisfies the orthogonal condition

$$\sum_{x=0}^{N-1} t_m(x) t_n(x) = \rho(n, N) \delta_{mn}, \quad (8)$$

$$0 \leq m, n \leq N-1$$

The scale factor $\beta(n, N)$ is usually a function of N which grows at the speed of N^n . The simplest form of $\beta(n, N)$ can be

$$\beta(n, N) = N^n \quad (9)$$

To make the scaled polynomial set orthogonal, $\beta(n, N)$ is given by

$$\beta(n, N) = \sqrt{\rho(n, N)} \quad (10)$$

then we define the Tchebichef moment as

$$T_{pq} = \frac{1}{p(p, N)p(q, N)} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} t_p(x) t_q(y) f(x, y) \quad (11)$$

$$p, q = 0, 1, 2, \dots, N-1$$

One method being used commonly to make computation of moments less demanding for the processor is the recurrence relation. The three-term recurrence relation of the weighted Tchebichef Polynomial with respect to n is defined as

$$(n+1)t_{n+1}(x) - (2n+1)(2x-N+1)t_n(x) + n(N^2 - n^2)t_{n-1}(x) = 0, n = 1, 2, \dots, N-1 \quad (12)$$

III. CHINESE CHARACTER RECOGNITION

Our primary task is to find efficient lower order Tchebichef moment feature functions to distinguish Chinese characters more effectively. In the view of statistics, moments with higher variance values have more power to differentiate objects. In order to select the best Tchebichef moment descriptors, we firstly calculated the variance values of lower order Tchebichef moments of a set of 6,763 Chinese characters defined in China's national standard GB2312, with the font of *song*. All of these Chinese characters are binary images with a size of 24×24 .

TABLE I: VARIANCE VALUES OF LOWER ORDER TCHEBICHEF MOMENTS T_{mn}

	0	1	2	3
0	0.7964	0.3664	0.8670	0.6905
1	0.2426	0.2083	0.3496	0.3042
2	0.4722	0.2643	0.4720	0.3962
3	0.2317	0.2038	0.3450	0.3247

Based on the variance values of 16 lower order Tchebichef moments shown in Table I, we have selected the highest four variance values as our four-dimensional Tchebichef moment

feature vector

$$\mathbf{V}[\mathbf{f}_1 = T_{00}, \mathbf{f}_2 = T_{02}, \mathbf{f}_3 = T_{03}, \mathbf{f}_4 = T_{20}] \sqrt{a^2 + b^2} \quad (13)$$

To measure the distance between any pair of Chinese characters in our four-dimensional Tchebichef moment feature space, the Euclidean distance is adopted as our measurement

$$d(\mathbf{f}_i, \mathbf{f}_j) = \sqrt{(f_{i1} - f_{j1})^2 + (f_{i2} - f_{j2})^2 + (f_{i3} - f_{j3})^2 + (f_{i4} - f_{j4})^2} \quad (14)$$

where $\mathbf{i}$ and $\mathbf{j}$ represent any two Chinese characters, $i, j \in [1, 6763]$.

In our experiment, the distances between all pairs of Chinese characters, $(6763 \times 6762)/2 = 22,865,703$ in total, are calculated.

TABLE II: THE TEN PAIRS OF CHINESE CHARACTERS WITH THE CLOSEST DISTANCE

	禛玎	沪耕	伟偃
$d_{ij}(T)$	1.9425	2.3142	2.0167
$d_{ij}(L)$	0.2436	0.3946	0.2758
	危簪	阍蹉	锂蛤
$d_{ij}(T)$	1.5746	1.6748	2.0435
$d_{ij}(L)$	0.1754	0.3241	0.3157
	恐醒	冥蜓	胛簌
$d_{ij}(T)$	1.8564	1.7493	1.3465
$d_{ij}(L)$	0.1564	0.1443	0.1647
	祥砑		
$d_{ij}(T)$	1.6984		
$d_{ij}(L)$	0.2546		

For comparison, we have formed a four-dimensional Legendre moment vector with the same selection process leading to (13). Table II shows the ten pairs of Chinese characters that have the closest distances in the four-dimensional Tchebichef moment space, compared by their distances in the Legendre moment vector space.

The $(p+q)$ th order Legendre moment is defined as:

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-1}^1 \int_{-1}^1 P_p(x) P_q(y) f(x, y) dx dy \quad (14)$$

where $P_p(x)$ is a Legendre polynomial of order p , which is defined as:

$$P_p(x) = \sum_{j=0}^p C_{pj} x^j \quad (15)$$

And

$$C_{pj} = \begin{cases} (-1)^{(p-j)/2} \frac{1}{2^p} \frac{(p+j)!}{[(p-j)/2]! [(p+j)/2]! j!}, & \text{if } p-j \text{ is even} \\ 0, & \text{if } p-j \text{ is odd} \end{cases}$$

Legendre polynomials form a complete orthogonal basis within the range of $[-1, 1]$.

TABLE III: DISTANCES ON SOME CHINESE CHARACTERS PAIRS WHICH ARE CLOSE IN STRUCTURES AND ARE DIFFICULT TO BE RECOGNIZED BY SOME SYSTEMS

	粘钻	借借	排排
$d_{ij}(T)$	8.5463	8.6748	9.0346
$d_{ij}(G)$	1.8629	2.1676	4.2597
	扬扬	倍培	入入
$d_{ij}(T)$	7.5786	8.3564	8.9785
$d_{ij}(G)$	3.5059	2.8710	2.4462
	饕饕	千于	大太
$d_{ij}(T)$	8.6947	7.9836	7.5492
$d_{ij}(G)$	2.0407	4.7123	3.3850
	大犬	未未	观现
$d_{ij}(T)$	8.3154	6.9827	6.8749
$d_{ij}(G)$	5.5103	0.7676	2.9021
	沙抄	垃拉	如知
$d_{ij}(T)$	8.0645	8.1674	7.2957
$d_{ij}(G)$	1.7538	2.9099	4.8679
	借借	拒拒	扑扑
$d_{ij}(T)$	7.8347	8.2495	7.6948
$d_{ij}(G)$	2.1676	3.3237	2.4950
	惜错	诗待	听听
$d_{ij}(T)$	9.3165	9.0442	8.5664
$d_{ij}(G)$	3.2325	1.3912	2.1927
	尸尸	天天	木木
$d_{ij}(T)$	8.5463	8.6748	9.0346
$d_{ij}(G)$	3.3113	2.0222	0.7212
	王玉	王主	论论
$d_{ij}(T)$	7.5786	8.3564	8.9785
$d_{ij}(G)$	0.6923	2.4831	4.7783
	今令	茶茶	伦抡
$d_{ij}(T)$	8.6947	7.9836	6.5814
$d_{ij}(G)$	1.2917	1.7076	1.7568
	日曰	夫失	井井
$d_{ij}(T)$	8.3154	6.9827	6.8749
$d_{ij}(G)$	1.1453	1.3932	2.4308
	毋母	万方	竟竟
$d_{ij}(T)$	8.0645	8.1674	7.2957
$d_{ij}(G)$	1.6591	1.7066	0.4604
	怕帕	奖浆	捡俭
$d_{ij}(T)$	7.8347	8.2495	7.6948
$d_{ij}(G)$	0.8103	5.2217	4.4499

The results shown in Table II indicate that by using the discrete Tchebichef moment vector, every pair in the set of 6,763 Chinese characters can be distinguished significantly.

We would like to mention that all of the ten closest pairs characters may be recognized without difficulty by other existing Chinese character recognition systems.

One of the most challenging tasks for Chinese characters recognition is to recognize some of Chinese characters that share similar structures. To address this issue, we have selected a set of Chinese character pairs which are difficult to be distinguished by other systems.

$d_{ij}(T)$ measures the distance using discrete Tchebichef moments method while $d_{ij}(G)$ measures the distance using orthogonal Gegenbauer moments method[17].

The results shown in Table III indicate that the four-dimensional Tchebichef moment based vector perform very well for all of these Chinese character pairs.

IV. CONCLUSION

A Chinese character recognition system with the Tchebichef moment-based method is described in this paper. Four Tchebichef moments with the largest variance values are selected to form a four-dimensional feature vector for the system. A set of 6,763 Chinese characters is used as the testing set, with each character has the size of 24×24 pixels. The results show that by using Tchebichef moment-based features, each pair of the testing Chinese characters can be distinguished significantly.

For the ten pairs of Chinese characters which are most difficult to be distinguished with the proposed system, they have very different structures and can be recognized by other existing system efficiently. On the other hand, some Chinese characters pairs with very similar structures can be easily recognized by our system. Therefore, our proposed Tchebichef moment-based recognition system can be applied as a complementary scheme with other Chinese character recognition systems to increase the successful recognition rate.

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